Automated Checking of Scaffold Safety Regulations using Multi-Class 3D Segmentation

J. Kim[a], J. Kim[a], N. Koo[a] and H. Kim[a]

[a]Department of Civil and Environmental Engineering, Yonsei University, Korea
E-mail: john101010@yonsei.ac.kr, kah5125@yonsei.ac.kr, ahappyto@gmail.com, hyoungkwan@yonsei.ac.kr

Abstract

Scaffolds, one of the most widely used temporary structures, are prone to safety-related accidents. Despite the fact, checking regulations for a scaffold is manually being conducted, which is inefficient, especially for a large construction site. This paper proposes an automated method to check safety regulations regarding scaffolds on sites. 3D point cloud data obtained from Terrestrial Laser Scanning (TLS) is first processed by a deep learning-based 3D segmentation to automatically identify major entities Then, a simple rule-based algorithm is applied to the segmented data to check for three types of major safety-related regulations. The result of our experiment shows potential for successfully automating scaffold safety checking at a construction site.

Keywords –

Deep learning; Scaffold; Point cloud; Semantic Segmentation; Safety regulation checking; Terrestrial Laser Scanning (TLS)

1 Introduction

Korea Occupational Safety and Health Agency's 2021 report on industrial accidents shows that the construction industry has the highest number of occupational deaths, constituting 50.6% of those of all industries [1].

One of the major reasons for those accidents are caused by temporary structures such as scaffolds [2]. Scaffolds are, due to their temporary nature, often not seriously considered and are prone to safety-related accidents [2]. It is, thus, necessary to check scaffolds on sites for violations of safety regulations. However, manual observation can be time-consuming and inaccurate, especially for large-scale construction sites.

Point cloud data acquired by laser scanning contain rich 3D geometric information of a site or an object. Pioneering studies, such as [3], demonstrated how TLS data can be processed in relation to CAD data. TLS data were also proven to have potential for safety regulation checking of scaffolds [4]. Recent advancement of deep learning technology on point clouds such as [5] allowed for a more effective segmentation of scaffold point cloud data from a large-scale construction site [6].

The proposed methodology fully automates the safety-related regulation checking process of scaffolds on construction sites. Thanks to deep learning-based point cloud segmentation and rule-based algorithm, multi-class segmentation and safety regulation checking of scaffolds are successfully conducted.

2 Methodology

The proposed methodology is divided into two parts: multi-class segmentation and regulation checking. For multi-class segmentation, point cloud data of a construction site acquired by a terrestrial laser scanner (FARO m70) are used as the input of RandLA-Net [5]. RandLA-Net used in this study is trained to classify each point into one of six classes: 'stairs,' 'work platform,' 'uprights,' 'guard rail,' 'bracing,' and 'background.' For regulation checking, a simple and robust rule-based algorithm is used to check if the scaffold violates safety regulations. The safety regulations to be used were selected based on the Korea Occupational Safety & Health Agency safety work guidelines on steel pipe scaffold (KOSHA Guide C-30-2020 [7]) and modular scaffold (KOSHA Guide C-32-2020 [8]). Details of the regulations are shown in Table 1.

Table 1. Considered Regulations

#	Regulations
I	Attachment status of working platforms
II	Attachment status of stairs
III	Attachment status of guard rail

2.1 Multi-Class 3D Segmentation

RandLA-Net is a neural architecture structured for efficient 3D semantic segmentation on large-scale point clouds by using random sampling instead of complex point selection approaches. By using a local feature aggregation module, RandLA-Net can capture complex local structures [5]. RandLA-Net has proven to effectively extract small entities from large scenes by showing high performance [5] on the Semantic3D dataset [9], a dataset of terrestrial laser scans of outdoor scenes. Previous study also proves the high performance of RandLA-Net when capturing features of scaffolds in large construction sites [6].

The RandLA-Net used in this study is composed of five sets of encoding and decoding layers. For the transfer learning, pre-trained parameters trained with the Semantic3D dataset were used as initial parameter values. Then, the network was fine-tuned by re-training the parameters of the inner six layers of the encoder and decoder.

2.2 Regulation checking algorithm

To check regulations of Table 1 with labeled outputs of RandLA-net, a representative 'uprights' coordinate (x and y) is first determined for each 'uprights' of the scaffold by peak finding based on the point density. The height (z-value) of each 'work platform' is also determined as the floor height from the data distribution. Then, potential fields of 'work platform' and 'guard rail' are calculated on the x-y plane based on the 'upright' coordinates by using the standard width of scaffolding entities. Figure 1 shows the potential fields of 'work platform' and 'guard rail'

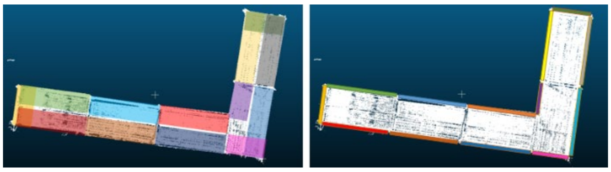

Figure 1. Potential fields of 'work platform'(left) and 'guard rail'(right); Different color shows different potential field instances.

2.2.1 Checking for Regulations Ⅰ & Ⅱ

Using the floor heights, 3D bounding boxes of potential fields for platforms are defined on each floor. To check regulation Ⅰ (attachment status of working platforms), the 'work platform' points need to be extracted to see if there are enough points within each box. If a bounding box turns out to have no work platform, it is now time to check regulation Ⅱ (attachment status of stairs). That is, the same bounding box is searched to see if there exists 'stairs' class points. The checking flow is shown in Figure 2.

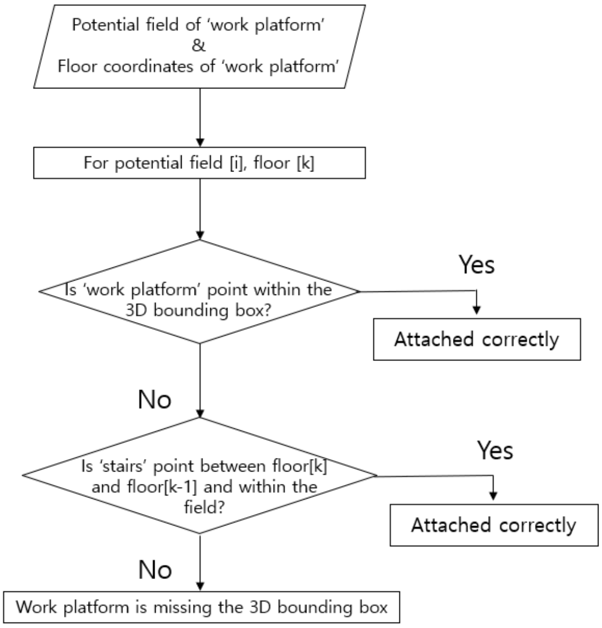

Figure 2. The checking flow for regulations Ⅰ & Ⅱ in a 3D bounding box.

2.2.2 Checking for Regulation Ⅲ

A 3D bounding box for 'guard rail' is generated using potential fields of 'guard rail' and the z-values between two floors. On each bounding box, the presence of 'guard rail' class points is checked for regulation Ⅲ (attachment status of guard rail). The checking flow is shown in Figure3.

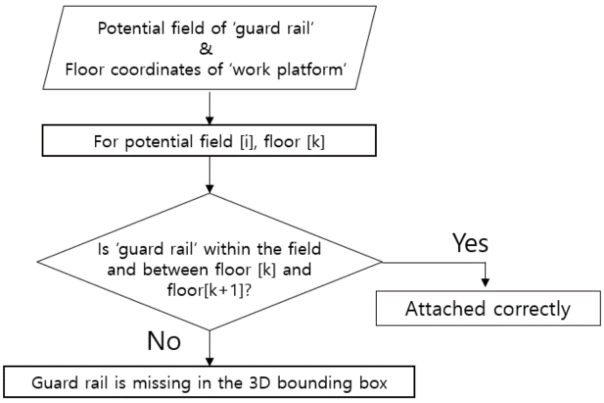

Figure 3. The checking flow for regulation Ⅲ in a 3D bounding box.

3 Experiments and Results

3.1 Dataset preparation

The dataset used in the experiments were acquired using FARO m70 from four different construction sites as shown in Figure 4. A total of fifteen registered point clouds acquired from Sites A, B, and C were used to train RandLA-Net. Each point cloud data were labeled to represent a total of six classes: 'stairs,' 'work platform,' 'guard rail,' uprights,' 'bracing,' and 'background.' Data acquired from Site D were used for the testing. Total number of points in the training and testing data were 103,223,397 14,649,928 points, respectively.

Figure 4. Upper left; Site A, Upper right; Site B, Lower left; Site C, Lower right; Site D.

3.2 Evaluation metrics

To effectively calculate the performance of each class, Precision, Recall, and F1-score were used. As shown in Equations (1) ~ (3), Precision is a metric that calculates the percentage of ground truth labels within the predicted truth labels. Recall is a metric that calculates the percentage of predicted truth labels within the ground truth labels. Most importantly, F1-score is a metric that calculates the harmonic average of Precision and Recall.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

3.3 Segmentation performance

All parameters of RandLA-Net, except for the training epoch, followed the setting of [6]. The training epoch was set as 50 considering the trend of training loss.

The results of multi-class segmentation by RandLA-Net are shown in Table 2. The results were evaluated taking an average of eight experiments with the same dataset and parameters. Class 'background' had the best F1-score of 98.83% followed by other successful segmentation results from 'uprights' 69.10%, 'guard rail' 68.95%, 'work platform' 61.14%, and 'stairs' 61.06%. Most of the false predictions of those five classes were found on the lower part of the scaffold. The 'bracing' segmentation results showed the poor performance with an 16.90% F1-score. This performance indicated a need for further studies if a need exists for regulation checking regarding bracings. Figure 5 shows a segmentation result.

Table 2. Segmentation results of RandLA-Net

Class	Precision (%) Recall (%)	F1 score (%)
'stairs'	66.56 62.18	61.06
'work platform'	74.87 51.92	61.14
'guard rail'	93.11 55.89	68.95
'uprights'	77.09 63.37	69.10
'bracing'	14.23 29.80	16.90
'background'	98.19 99.48	98.83

3.4 Results and discussions

According to the regulation checking algorithms, both 'work platform' and 'guard rail' had thirteen potential fields on the x-y plane (shown in Figure 1), and the number of floors was one. The results for the three regulations can be summarized as shown in Table 3. The two violations of regulation Ⅲ are shown as yellow line in the last picture of Figure 5. They were all accurately predicted by the proposed method.

The regulation checking algorithm was focused on scaffold entities containing 'stairs,' 'work platform,' 'guard rail,' and 'uprights.' The misclassified points of 'bracing' could be filtered by following the steps of the regulation checking algorithm. This allowed the poor segmentation result of 'bracing' to not affect the final performance of the regulation checking process.

The scaffold of Site D was an L-shaped scaffold, which was not contained in Sites A, B, and C. This shows a robust performance of our model regarding the shape of a scaffold. However, there is still a need to enrich the dataset to improve segmentation results and generalize the proposed methods at other construction sites. Data acquisition of this study was limited especially because of the temporary nature of scaffolds. Ablation studies of generating synthetic data could help to address this problem and improve the model generalization.

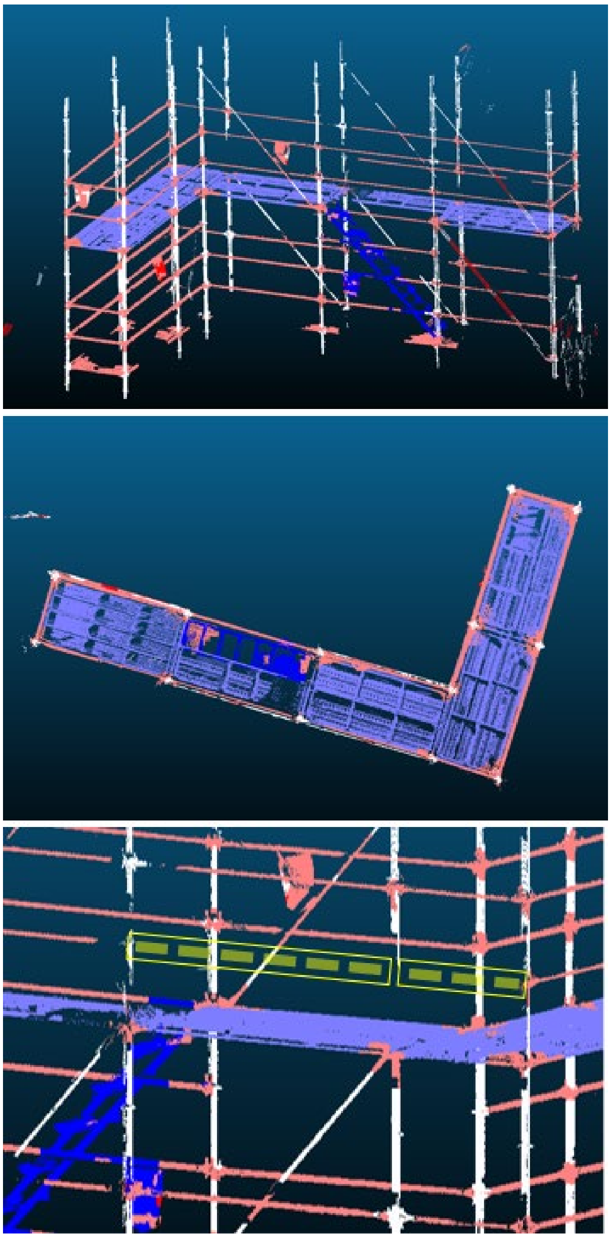

Figure 5. Visualization of segmentation results; {blue: 'stairs', purple: 'work platform', pink: 'guard rail', white: 'upright', red: 'bracing'}

4 Conclusion

This study presented a fully automated methodology to accurately check three major safety scaffold-related regulations specified in the KOSHA Guide to scaffolds [7, 8]. The proposed methodology is composed of a deep learning-based point cloud segmentation (RandLA-Net) and rule-based algorithms. The segmentation F1 scores were 98.83% for 'background,' 69.10% for 'uprights,' 68.95% for 'guard rail,' 61.14% for 'work platform,' 61.06% for 'stairs,' and 16.90% for 'bracing,' respectively. They were sufficient to successfully check all three major regulations considered on this study. These results indicate that this methodology has high potential to fully automate safety monitoring of scaffolds which will lead to a significant reduction in accidents and deaths in the construction industry.

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Table 3. Results for the three regulations (G.T.: ground truth, O: normal, X: violated, -: not to be considered)

	Potential field	1	2	3	4	5	6	7	8	9	10	11	12	13
Regulation I	Prediction	O	O	X	O	O	O	O	O	O	O	O	O	O
	G.T.	O	O	X	O	O	O	O	O	O	O	O	O	O
Regulation II	Prediction	-	-	O	-	-	-	-	-	-	-	-	-	-
	G.T.	-	-	O	-	-	-	-	-	-	-	-	-	-
Regulation III	Prediction	O	O	O	O	O	O	O	O	O	X	X	O	O
	G.T.	O	O	O	O	O	O	O	O	O	X	X	O	O

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